Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Engineering 41 (2012) 833 – 837
Engineering Procedia
www.elsevier.com/locate/procedia

International Symposium on Robotics and Intelligent Sensors 2012 (IRIS 2012)

# Shadow Removal Using B-spline for Edges Reconstruction in Surveillance

Redwan A.K. Noaman*, Mohd. A. Mohd. Ali, Kasmiran Jumari

*Department of Electrical, Electronic and Systems Engineering- Faculty of Engineering and Built Environment*
*43600 Bandar Baru Bangi, Universiti Kebangsaan Malaysia, Selangor, Malaysia*

**Abstract**

Shadows are one of the major problems in objects detection and tracking for automated video surveillance systems. In such systems accurate detection is required even under variable weather conditions. The majority of shadow removal algorithms in the literature suffer from misclassification errors because of inaccurate shadow detection, thus resulting in distorted object shapes. In this paper, a novel technique is proposed for shadow detection and removal using both edge detecting and B-spline algorithm. This technique is capable of correcting such errors by using B-spline algorithm for object's edges reconstruction so that the object shapes remain well defined along most part of their contours. Experimental results in PETS2006 benchmark dataset show that the proposed technique increases the shadow detection reliability compared to some existing shadow detection algorithms.



*Keywords*: Shadows, Video Surviliance, Tracking.

## 1. Introduction

Automatic video surveillance applications require accurate detection for objects moving during the scene. One of the main challenges in the process of moving object detection is to differentiate moving objects from their shadows. Several foreground object detections are proposed such as background subtraction, optical flow and temporal differencing [1]. Shadows affect the process of foreground object detection. They cause many problems [2] in the object localization, segmentation, extraction of the objects and tracking. Furthermore, shadows may cause merging of objects with each other; objects shapes may be distorted; the background may be classified as foreground and missing objects.

In computer vision systems, all stages are connected; and later processing stages depend on previous stages. In other words, it is very important to overcome shadow problems to get accurate results in next stages like objects classification and tracking.

Nowadays, several shadow detection techniques have been developed [2]; and they can be classified by their use of chromaticity information [3-5], edge information [6], stereo information or a combination of them [7]. Despite all recent research in this area, most current real time shadow techniques depend on color information and working at pixel level. Many techniques are based on making certain assumptions [8] about the shadow properties like:

(i) A shadow darkens the background area on which it falls
(ii) A shadow only falls on the ground plane
(iii) A shadow changes luminance of an area significantly but does not impact color much.

* Corresponding author. Tel.: +6-017-621-2103
*E-mail address:* redwan_eng@yahoo.com

1877-7058 © 2012 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.
doi:10.1016/j.proeng.2012.07.251

Color based techniques suffer from many problems like misclassification; and the failure may accrue because of the assumptions which do not suit all scenarios or because of foreground objects possesses or parts which have similar features as the shadow.

Hence, using color information only for shadow detection is not enough for accurate results. Recent literature shows a trend towards the use of texture information or region level processing for the shadow detection [3-6], also shadow detection techniques use the properties which come out from the shadows like edges [9] background texture [10].

Some techniques for shadow detection use classifiers which need to be trained with labeled data. In real time applications, the availability, annotation, and amount of training data are critical issues [13]. Besides, some techniques are developed [3-4] to work without a need for training data and to avoid the problems mentioned above.

In this paper, a method for shadow removal and detection is proposed. It is based on objects edges information and B-spline algorithm for edges reconstruction. It works without a need for training or modelling stages.

## 2. Shadow Removal and Detection Algorithm

### *2.1. Background Initialization*

Background reference image has been produced based on [11] a method that is adaptive, reliable and computationally not very complex. The idea behind the algorithm is to use a Modal calculation. It depends on the intensity value of the pixel. Where a value appears most often, it indicates that it has much redundancy during training sequences; and it should be the value which represents the background model for that pixel. A history map is created for all the pixels, and then a reference background image is produced through a Modal calculation for each pixel history on the history map.

### *2.2. Shadow Detection and Removal*

The next stage after getting a background reference image *(BR)* is to deal with shadow in the current frame of the sequence; shadows cast on the background and changes its color information; that is why a Blue band from RGB color model is chosen to be the main band in our method. The RGB color model shows shadow effects less significant in the Blue band.

First, the Blue band of the background reference image $BR_{blue}$ is taken and moved to normalization process. Then, the Blue band of the current frame $CF_{blue}$ is taken and subtracted from $BR_{blue}$; the resulting image is $S_{blue}$. Then, a threshold is applied for $S_{blue}$ to remove noise; and the resulting image is $SB_{th}$.

It is assuming that the edges of the objects are not changed because objects often have strong edges than their shadows specially when using Blue band of RGB Model. Based on that, a Prewitt edge filter is applied to get the edge information from SBth. The Prewitt filter is chosen because it produces clear edges and is more reliable to show the regions where the intensity changes. It contains 3x3 kernel in both directions x and y and the resulting edges will be the magnitude of edges in both directions. This Prewitt filter will be convolved with $SB_{th}$ :

$$Mx=\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \qquad My=\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

Fig. 1. Illustration the output of Prewrite filter applied to $SB_{th}$.

Fig. 1 shows an example of edge detection using the Prewitt edge detector. As shown in Fig. 1, the edges of the objects suffer from some disconnected points. In order to overcome this problem, B-spline algorithm is used. A spline curve is a sequence of curve segments that are connected together to form a single continuous curve. For this reason, in proposed method, the B-spline technique has been used to reconstruct the edges for the objects which may disconnect and get distorted through previous stages for shadow removal.

B-spline algorithm goes through the whole image using a special kernel [15*30] and determines maximum number of edge points in each kernel. If the number of points is smaller than certain threshold, this means there is small connectivity. Then, B-spline works and connects the points in that kernel. If the number of points is greater than certain threshold, it means there is more connectivity and common borders within that kernel. Then, this assumes the edges in that kernel is connected properly and no need to use B-spine there. The same steps are repeated until the special kernel moves to the end of the image. Finally, some morphological processes (Dilation, Erosion and Filling) applied to finish up the proposed algorithm and extract the foreground objects without shadow effects.

## 3. Results and Discussion

To evaluate the effectiveness of the proposed method, the proposed method was compared with two methods: Horprasert's method [12] and Conaire's method [3]. Horprasert's method detected shadow by proposing a computational color model that separates the brightness component from the chromaticity component; shadow was identified as pixels that have similar chromaticity but lower brightness than the corresponding pixels in the background image. Conaire's method was based on the maximization of the agreement between two independent shadow detectors (Luminance & Saturation) without training data, however, appropriate thresholds were automatically chosen for shadow detection.

An example for the comparison results is shown in Fig. 2. Images were carefully chosen to show the performance for compared methods where the shadows appear strongly. Whenever the shadows appear strongly that means it will be more difficult to be removed because shadows will be similar to the foreground objects or merged with some parts of it. In Fig. 2. a, the original images are presented which were manually annotated to show foreground objects in Blue color and shadows in Red color. Fig. 2.b shows the results of Horprasert's method, even though this method removes some parts of shadows but still cannot fully remove all shadows effects. Fig. 2.c shows the results of Conaire's method which performs better than the first one, where the number of error pixels decreases; however it still suffers from strong shadows effect. Fig. 2.d shows the results of the proposed method where the effect of shadows is almost fully removed; and the foreground objects can be extracted or processed successfully.

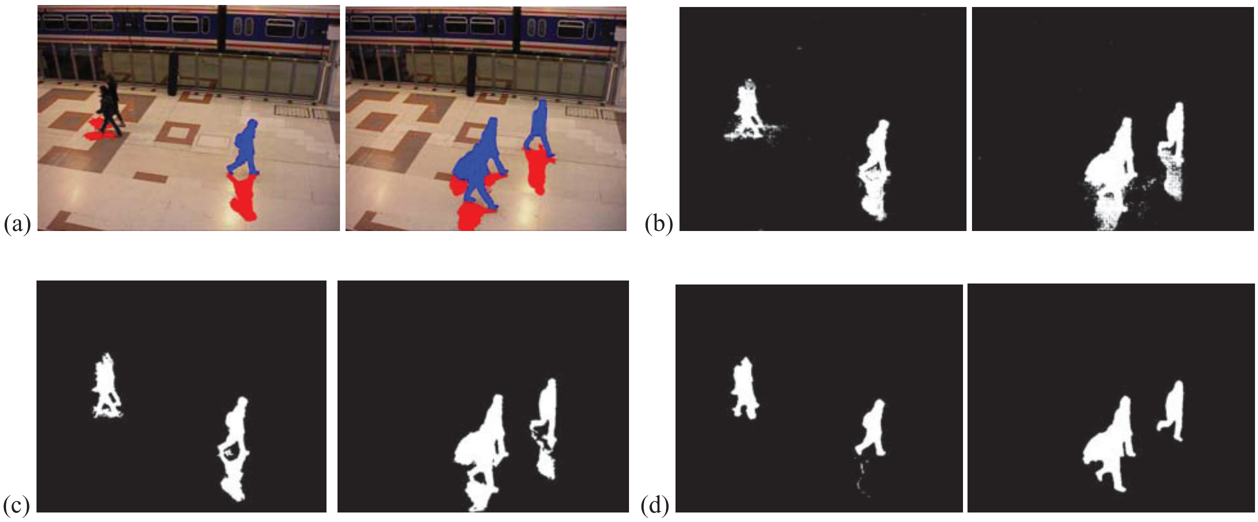


Fig. 2. Illustration of comparison for shadow removal (a) Original Image (Foreground Object is blue, Shadow is red) (b) Output of Horprasert's method (C) Output of Conaire's method (d) Output of proposed method.

Furthermore, another comparison with previous methods was performed and the results shown in Fig.3. A sequence of 20 Frames contains shadow effect taken from PETS2006. All foreground objects without shadows for each frame were manually annotated and converted to white color to work as a reference frames for pixel by pixel comparison. Same 20 Frames were processed frame by frame with Horprasert's method, Conaire's method and the proposed method. Each result for every frame from each method was compared pixel by pixel with the reference frame and the error pixels were counted for each frame as shown in Fig.3 which shows that the proposed method performs better because it achieved the minimum number of error pixels.

As shown in Fig. 2 and 3. the proposed method shows better performance; and the advantages of the proposed method can be summarized as follows:

- Proposed method is more flexible and applicable for real events for surveillance
- Proposed method gives less number of error pixels
- Proposed method requires less processing time because it works without a need for a training stage.

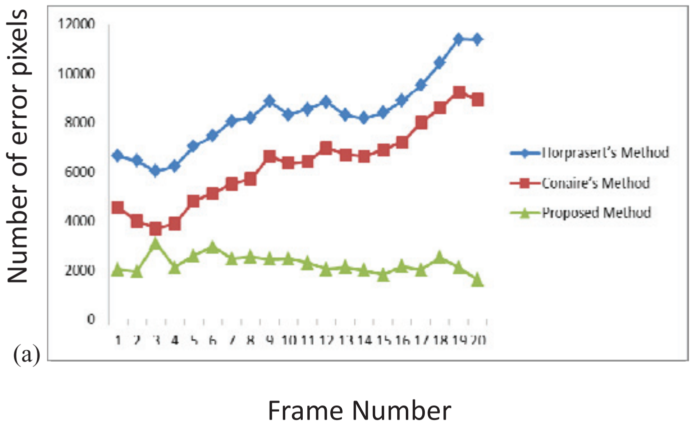


Fig. 3. Illustration of the comparison results for the number of error pixels for each frame .

## 4. Conclusion

In this paper, a new technique for shadow detection and removal in surveillance is proposed. It works directly without training data or creating a model, thus it needs less computational cost. It is based on edges information for the moving objects and utilizes the advantage of B-Spline algorithm to perform objects edges reconstruction. Experimental results show that the proposed technique is easy to implement, robust and efficient for shadow removal in surveillance scenarios using static cameras. Moreover, the proposed technique works in real time and can be used in any video surveillance systems to increase the accuracy and robustness for the next stages like segmentation and tracking.

## Acknowledgements

The authors would like to thank Universiti Kebangsaan Malaysia (UKM) for supporting this project under grant (UKM-AP-TKP-07-2009).

## References

[1] A. Yilmaz, O. Javed, M. Shah, 2006. Object Tracking: A Survey, ACM Computing Surveys 38, p. 45.

[2] A. Prati, I. Mikic, M. M. Trivedi, R. Cucchiara, 2003. Detecting Moving Shadows: Algorithms and Evaluation, IEEE Transaction On Pattern Analysis and Machine Intelligence 25, p. 918.

[3] Conaire, C., O'Connor, N., Smeaton A., 2007. "Detector adaptation by maximising agreement between independent data sources" Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp.1-6.

[4] Cucchiara, R., Grana,C., Piccardi,M., Prati,A., 2003. Detecting Moving Objects, Ghosts and Shadows in Video Stream, IEEE Transaction On Pattern Analysis and Machine Intelligence 25, p. 1342.

[5] Tattersall, S., Dawson-Howe, K., 2003. “Adaptive shadow identification through automatic parameter estimation in video sequences” Proceedings of Irish Machine Vision and Image Processing Conference, pp. 57-64.
[6] Xu D. Liu, J. Li, X. Liu, Z. Tang X., 2005. Insignificant Shadow Detection for Video Segmentation, IEEE Transaction on Circuits and Systems for Video Technology 15, p. 1058.
[7] Yang, M.-T. Lo, K.-H. Chiang, C.-C. Tai, W.-K., 2008. Moving Cast Shadow Detection by Exploiting Multiple Cues, IET Image Processing 2, p. 95.
[8] Muhammad Shoaib, Ralf Dragon, Jorn Ostermann, 2009. “Shadow detection for moving humans using gradient-based background subtraction” IEEE International Conference on Acoustics Speech and Signal Processing, pp. 773-776
[9] O. Javed, M.Shah, 2002. “Tracking and object classification for automated surveillance” The seventh European Conference on Computer Vision, pp. 343-357.
[10] G.D.Finlayson, S.D. Hordley M.S.Drew, 2002. “Removing shadows from images” The seventh European Conference on Computer Vision, pp. 823-836.
[11] Redwan A.K. Noaman, M. Ali, and K. Jumari, 2009. Background Model Initialization using Modal Algorithm for Surveillance, International Journal of Intelligent Information Technology Application 2, p. 294.
[12] T. Horprasert, D. Harwood, L.S. Davis, 2000. “A robust background subtraction and shadow detection” Proceedings of the ASIAN conference on Computer Vision.
[13] Nadimi, S., and Bhanu, B., 2002. “Moving shadow detection using a physics based approach” Proceedings IEEE International Conference Pattern Recognition, pp. 701–704